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Hybrid Evolutionary Algorithm-based Schemes for Subcarrier, Bit, and Power Allocation in Multiuser OFDM Systems

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1. Introduction

Multiuser orthogonal frequency division multiplexing (OFDM) is a very promising multiple access technique to efficiently utilize limited RF bandwidth and transmit power in wideband transmission over multipath fading channels. When a wideband spectrum is shared by multiple users in multiuser OFDM-based systems, different users may experience different fading conditions at all subcarriers. Each user is assigned a subset of all subcarriers by some allocation algorithm. Thus, multiuser diversity can be achieved by adaptively adjusting subcarrier, bit, and power allocation depending on channel status among users at different locations (Wong et al., 1999a). In (Wong et al., 1999a), Wong applies a Lagrangian optimization technique and an iterative algorithm to solve the subcarrier, bit and power allocation problem. The suboptimal scheme for the NP-hard joint optimization problem is decoupled into two steps while it has a high computational complexity. A sub-optimal algorithm has been proposed to solve a related problem (Wong et al., 1999b). In (Wong et al., 1999b), Wong presents a real-time subcarrier allocation (SA) algorithm. It is a two-phase algorithm, including the constructive initial assignment (CIA) and the subcarrier swapping steps. The initial subcarrier allocation algorithm needs to pre-determine the numbers of subcarriers for each user before the allocation process starts. The performance of the SA-based algorithm will be compared in the simulation. In (Kim et al., 2006), Kim shows that the allocation problem in (Wong et al., 1999a) can be transformed into an integer programming (IP) problem. The branch-and-bound algorithm (Wolsey, 1998) can be employed to find the optimal solution of the allocation problem which has exponential computational complexity in the worse cases. We utilize the approach to obtain the optimal solution as the performance bound for comparison.
Evolutionary algorithms (EA) are used to solve extremely complex search and optimization problems which are difficult to solve through simple methods. EAs are intended to provide a better solution, as it is based on the natural theory of evolution. Evolutionary algorithm (EA)-based schemes have been applied to solve subcarrier, bit, and power allocation problems (Wang et al., 2005) (Reddy et al., 2007) (Reddy & Phora, 2007) (Pao & Chen, 2008). In general, chromosomes can be designed with binary, integer, or real representation. The chromosome lengths are related to the number of subcarriers. Each element in the chromosome is a subcarrier allocated to a user. In this research, a subset of subcarriers can be assigned to one user depending upon the availability of subcarriers at a particular time

(Wong et al., 1999a) (Wong et al., 1999b) (Kim et al., 2006) (Wang et al., 2005) (Reddy et al., 2007) (Reddy & Phora, 2007) (Pao & Chen, 2008). In the methods (Wang et al., 2005) (Reddy et al., 2007) (Reddy & Phora, 2007), chromosomes with "good" genes are added in the initial population to improve the convergence rate. This concept is also adopted in the scheme (Pao & Chen, 2008) which generates a chromosome with good genes by employing the CIA method (Wong et al., 1999b) in the proposed ES-based schemes. It is believed that a better initial subcarrier assignment could achieve better performance (Wang et al., 2005) (Reddy et al., 2007) (Reddy & Phora, 2007) (Pao & Chen, 2008). The ES-based scheme (Pao & Chen, 2008) uses the integer representation for the solutions. In this paper, an encoding scheme is discussed about the mapping between the binary-string representation and the integer representation in the solution.

In this paper, a hybrid evolutionary algorithm (HEA) is proposed to solve the subcarrier, bit, and power allocation problem. The HEA is an EA-based approach coupled with a local search algorithm. The concept of a HEA can be found in (Miller et al., 1993) (Kassotakis et al., 2000) (Quintero & Pierre, 2008). A local search algorithm intends to perform optimization locally, while an EA tries to achieve optimum globally. There are two EA-based natural selection schemes (NSS), *NSS-I* and *NSS-II*, presented for the allocation problem and compared in this paper. *NSS-I* is a novel scheme proposed in the paper and *NSS-II* is adapted from (Wang et al., 2005). Every step of these two evolutionary algorithm-based natural selection schemes is addressed in details in this paper. The recombination operation in the proposed *NSS-I* considers the difference between two chromosomes. The recombination operation in *NSS-I* would re-assign a specific subcarrier to different users. A better solution could be found through the proposed natural selection scheme. The similarity and the difference between chromosomes are not considered in the recombination operation in *NSS-II* (Wang et al., 2005). It makes the recombination operation in *NSS-I* more efficient than that in *NSS-II* (Wang et al., 2005). One local refinement strategy is proposed to re-assign the "free" subcarriers to provide better performances, and aims to enhance the convergence rate. The simulation results show that the proposed hybrid evolutionary algorithm (HEA)-based scheme with the integer representation converges fast, and the performance is better and close to that of the optimum solution with the judicious designs of the recombination operation, the mutation operation, and the local refinement strategy. Besides, an adaptive scheme for time-varying channels is also proposed to provide competitive performance with the reduction of the population sizes and the number of generations.

2. System model

Assume the system has K users and N subcarriers. A subset of N subcarriers is assigned to a user, and the number of bits is also determined on downlink transmission. $\{h_{n,k}\}$ denotes the channel gains over all N subcarriers for the k-th user at subcarrier n. The number of bits of the n-th subcarrier assigned to user k is $r_{n,k}$. The required received power f_k at a particular data error rate is a function of bits per symbol $r_{n,k}$. It is not allowed a subcarrier is shared among different users. Therefore, we define

$$\rho_{n,k} = \begin{cases} 1, & if\ r_{n,k} \neq 0 \\ 0, & if\ r_{n,k} = 0 \end{cases} \tag{1}$$

The variable $\rho_{n,k}$ is either 1 or 0, and the sum of all $\rho_{n,k}$ is equal to 1 for any particular n. The required transmit power can be expressed as

$$P = \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{f_k\left(r_{n,k}\right)}{h_{n,k}^2} \rho_{n,k} \tag{2}$$

Data rates $\{R_1, R_2, ..., R_K\}$ are predetermined parameters for each user. The bit error rate must be ensured at a certain level to meet the service quality. The subcarrier, bit and power allocation problem for the minimization of total transmit power is formulated as

$$\underset{r_{n,k}, \rho_{n,k}}{Min} \quad \sum_{n=1}^{N} \sum_{k=1}^{K} \frac{f_k\left(r_{n,k}\right)}{h_{n,k}^2} \rho_{n,k}$$

$$subject\ to\ \sum_{k=1}^{K} \rho_{n,k} = 1,\ for\ n = 1, 2, ...N \text{ and } \sum_{n=1}^{N} r_{n,k} = R_k,\ for\ k = 1, 2, ..., K \tag{3}$$

This nonlinear optimization problem could be solved by employing integer programming (IP) (Kim et al., 2006). Therefore, the formulation to achieve the optimal bound for the performance comparison is briefly summarized as follows (Kim et al., 2006). If $r_{n,k} \in \{0, 1, ..., M\}$, then

$$f_k\left(r_{n,k}\right) \in \{0, f_k(1), ..., f_k(M)\} \tag{4}$$

A new indicator variable $\gamma_{n,k,r}$ is defined as

$$\gamma_{n,k,r} = \begin{cases} 1, & if\ \rho_{n,k} = 1 \text{ and } r_{n,k} = r \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where $r \in \{0, 1, ..., M\}$. For a particular subcarrier n, the value of $\gamma_{n,k,r}$ must be 0 or 1. $\gamma_{n,k,r}$ is an indicator. $\gamma_{n,k,r} = 1$ means that the nth subcarrier is assigned to the kth user with the rth modulation. $\sum_{r=0}^{M} \gamma_{n,k,r} = 1$ means that only one type of modulation is employed for that user. For other users, $\sum_{r=0}^{M} \gamma_{n,k',r} = 0$ because the nth subcarrier is not assigned to the other users. $\sum_{r=0}^{M} \gamma_{n,k,r}$ is either 1 or 0. Therefore, when more than one subcarrier (by observing different n) is assigned to one user, $\sum_{r=0}^{M} \gamma_{n,k,r}$ is either 1 or 0. The problem formulation is presented for the use of the branch-and-bound to solve the problem. It follows that (4) is rewritten as

$$f_k\left(r_{n,k}\right) = \sum_{r=0}^{M} \gamma_{n,k,r} f_k(r) \tag{6}$$

The required transmit power (2) can be re-expressed as

$$P = \sum_{n=1}^{N} \sum_{k=1}^{K} \left\{ \sum_{r=0}^{M} \gamma_{n,k,r} \frac{f_k(r)}{h_{n,k}^2} \right\} \rho_{n,k} \tag{7}$$

The indicators $\gamma_{n,k,r}$ and $\rho_{n,k}$ are related as

$$\rho_{n,k} = \sum_{r=0}^{M} \gamma_{n,k,r} \tag{8}$$

and we have

$$\gamma_{n,k,r} \cdot \rho_{n,k} = \gamma_{n,k,r} \ . \tag{9}$$

(7) is rewritten as a linear cost function:

$$P = \sum_{n=1}^{N} \sum_{k=1}^{K} \sum_{r=0}^{M} \gamma_{n,k,r} \frac{f_k(r)}{h_{n,k}^2} \tag{10}$$

A linear integer programming-based branch-and-bound algorithm (Wolsey, 1998) can be employed to solve this problem. In general, integer programming is a full-search approach which needs exponential time. Therefore, we proposed a suboptimal scheme to solve the subcarrier, bit, and power allocation problem for OFDMA systems.

3. Encoding schemes

One encoding scheme is required in the implementation of the EA-based schemes. Here, an encoding scheme is presented for the mapping of the possible solutions between the binary-string representation and the integer representation. In the proposed scheme, the chromosome lengths are related to the number of subcarriers. Each element in the chromosome contains a user index which means a subcarrier allocated to the user. A subset of subcarriers can be assigned to a user.

First, we introduce the encoding scheme with integer representations. Referring to Table 1, each chromosome represents one solution. The chromosome with *N* elements denotes a subcarrier assignment solution to the optimization problem. Each element in the chromosome represents a subcarrier assignment, and its value is coded as an integer at the range of 1 to *K* that stands for an index of a user. For example, the first element in the first chromosome is 2. It means that the 1st subcarrier is assigned to the 2nd user. The union of these chromosomes is called the population as shown in Table 1. The chromosome lengths of *N* are equal to the number of total subcarriers, and are not varied for different numbers of users. The size of the population should make the possible solutions diverse enough for finding the optimal solution.

N subcarriers

	1st	2nd	3rd	4th	5th	6th	7th	*N*th
Chromosomes	2	8	5	1	4	2	3	…
	1	3	6	2	2	4	1	…
	6	1	5	6	2	3	…	…
	4	…	…	…	…	…	…	…
	….	…	…	…	…	…	…	…

Table 1. The integer representation

In general, chromosomes can be designed with binary, integer, or real-valued representation. Encoding methods are discussed in details in (Coley, 2003). Referring to Table 1, we assume there are 8 users in the example. The number of bits for encoding the user index into the binary-string representation should be sufficient to fulfill the presentation needs associated with the number of users. For example, the maximum number of users which can be represented with 3 encoding bits is $2^3 = 8$.

User	1	2	3	4	5	6	7	8
Binary	000	001	010	011	100	101	110	111

Table 2. A typical example of the encoded binary-string representations for 8 users

Table 3 is an example of a three-bit encoding scheme for the mapping between the binary-string representation and the integer representation. By taking the first chromosome in Table 1 for example, the binary-string representation based on Table 2 is obtained as:

Subcarrier	1st	2nd	3rd	4th	5th	6th	7th	*N*th
Real	2	8	5	1	4	2	3	…
Binary	001	111	100	000	011	001	010	…

Table 3. A typical example of a three-bit encoding scheme

The encoded binary-strings are equally distributed among users. One or more than one encoded binary-string representations may be mapped to a particular user. Table 4 shows an example when the number of user is less than the number of the combinations with 3 encoding bits. Referring to Table 4, "000" and "001" stand for user 1; "010" and "011 stand for user 2; "100" and "101" stand for user 3; "110" and "111" stand for user 4. If each user has the equal number of the encoded binary-string representations, then it means each user has equal subcarrier assignment probability during the iteration process. Under some circumstances, each user would not have the same assignment probability, such as 6 users with 3 bits to encode. If the length of the binary-string associated with the number of bits is not long enough, the unequal assignment probability would happen. Long binary-string encoding is preferred with this mapping method. Other mapping method can also be designed to avoid this requirement of the long binary-string encoding such as the modulus operation.

User	1		2		3		4	
Binary	000	001	010	011	100	101	110	111

Table 4. A typical example of the encoded binary-string representations for 4 users

Note that the number of encoding bits is predetermined and related to the number of users. Both representations for the solution are able to be utilized in the following proposed EA-based allocation schemes.

4. Proposed evolutionary algorithm-based allocation schemes

The evolutionary algorithm (EA) (Back, 1996) (Spears, 2000) is proposed to search optimum solutions, which can be traced to at least the 1950s. Two typical approaches in evolutionary computing methodologies are "evolutionary strategy (ES)" and "genetic algorithm (GA)".

GA emphasizes on recombination process; ES makes use of both mutation and recombination procedures. The basic structure of the evolutionary algorithm consists of four operations, including selection, recombination, mutation, and fitness evaluation.

Fig. 1 illustrates the processing block diagram of the proposed HEA-based scheme in this paper. The scheme provided in Table 1 is one subcarrier for one gene to construct a chromosome and procedures are followed in all papers (Wang et al., 2005) (Reddy et al., 2007) (Reddy & Phora, 2007) (Pao & Chen, 2008). The encoding design can be integer, binary, or real-value. The subcarrier allocation method of Wong et al. (Wong et al., 1999b) is utilized to create one chromosome with good genes in the initial population, where the numbers of subcarriers are predetermined for all users. In this paper, one subcarrier for one gene and random allocation creates the other chromosomes in the initial population. The predetermined numbers of subcarriers for users would be adjusted while performing the proposed algorithm.

There are two natural selection schemes for the allocation problem presented in this paper. Every component of these two schemes is discussed in details as the following.

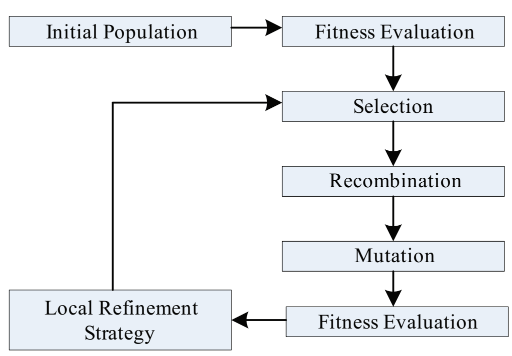

Fig. 1. Block diagram of the hybrid evolutionary algorithm-based scheme

A. Natural Selection Scheme I (NSS-I)

The natural selection scheme (*NSS-I*) is proposed for solving the allocation problem with the judicious designs of the recombination operation, the mutation operation, and the local refinement strategy.

A.1 Initialization of the Population

The initial population of size A_1 is composed of one chromosome generated by the CIA procedure (Wong et al., 1999b) and A_1-1 chromosomes created by randomization. The major merit of the CIA procedure is to select subcarriers with better channel conditions for the users according to the predetermined number of subcarriers per user. According to the CIA procedure (Wong et al., 1999b), the numbers of subcarriers assigned to users have to be determined in the beginning. However, in the problem under consideration, the optimum number of assigned subcarriers for each user is unknown. The numbers of subcarriers assigned to users are equal in the initialization phase. Note that the numbers of the subcarriers are temporarily preset in the initial population and they would be adjusted as the number of the generations increases for approaching those of the optimal solution. It does not mean the numbers of subcarriers for the final solution have to be determined in the beginning with the proposed scheme. Table 1 shows a typical example of the integer representation in the EA-based allocation scheme.

A.2 Selection

The fitness function is defined as the transmit power evaluated by a bit loading approach. After sorting, μ chromosomes associated with the μ largest values of fitness evaluation are selected from the population of size A_1, and saved in the mating pool, while the rest $A_1 - \mu$ chromosomes are deleted. The number of chromosomes μ that are kept in each generation is fixed. The new offsprings of size $A_2 = A_1 - \mu$ will be generated in the next step. The population size of $A_1 = \mu + A_1 - \mu$ to evaluate the fitness is not changed for each generation. Besides, the best one chromosome is kept independent at each generation in order to hold the convergence of the solutions. If the current best chromosome is superior to the one in the last generation, the best chromosome is replaced. The problem under consideration is to find the allocation solution which minimizes the transmit power. Due to the property of the minimization problem in communications with wireless channels under consideration, the scheme keeps one best chromosome to make the solution continue to improve in the sense of the minimization of power.

A.3 Recombination

Two chromosomes $\left(x_f, x_m\right)$ are randomly and iteratively selected from the mating pool of μ chromosomes to produce two new offsprings $\left(x'_f,\, x'_m\right)$ (Back, 1996) (Siu et al., 2005). The differences between genes are utilized in the recombination procedure. The rule can be represented as

$$x'_f \leftarrow x_f + g_r k\left(x_f - x_m\right) \text{ and } x'_m \leftarrow x_m + g_r k\left(x_f - x_m\right) \tag{11}$$

where the step size g_r has the inequality $0 < g_r \le 1$. The coefficient k is defined as

$$k = \begin{cases} 1, & if\ U(0,1) < p_c \\ 0, & if\ U(0,1) > p_c \end{cases} \tag{12}$$

where $U(0,1)$ is a value generated by a random number generator with the uniform distribution of [0,1]. From equation (11), some elements in chromosomes x_f and x_m would be changed if the genes are different. That is, a specific subcarrier is assigned to different users. The parameters, g_r and p_c, are used to change the value of the element in the chromosome, i.e. to re-assign a specific subcarrier to another user. A better solution could be found through the natural selection scheme. Note that elements in $\left(x'_f,\, x'_m\right)$ are rounded off to integers. The μ chromosomes and the new offsprings of size $A_2 = A_1 - \mu$ are merged to be a set of A_1 chromosomes for mutation.

A.4 Mutation

The concept of mutation is to prevent the solution trapped into a local minimum. Mutation points are randomly selected from the population of size A_1. The mutation probability P_m is defined by the fuzzy logic technique that provides an effective concept for dealing with the problem of uncertainty and imprecision (Lee, 1990). The fuzzy logic controller (FLC) is thus utilized based on this concept to provide the adaptive mutation probability during the optimization process. Average variance alleles (AVA) (Herrera et al., 1994) are used to determine the mutation probability. An AVA is employed to measure the difference among chromosomes by monitoring the population diversity and correlation. An AVA is a dynamic parameter in the process of the EA-based natural selection schemes. The mutation probability P_m is defined by the fuzzy logic controller (FLC) with the AVA parameter as following:

If the current AVA is greater than the averaged AVA, the mutation probability should increase and vise versa. AVA is calculated per each generation. AVA is low when the A_1 chromosomes are quite similar. The adaptive mutation probability adjustment scheme is given as the following:

$$P_m = \begin{cases} P_m + \delta \dfrac{AVA}{\overline{AVA}}, \ if \ AVA \geq \overline{AVA} \\ P_m - \delta \dfrac{\overline{AVA}}{AVA}, \ if \ AVA < \overline{AVA} \end{cases} \quad (13)$$

where $AVA = \sum_{j=1}^{N} \sum_{i=1}^{A_1} \left(\overline{S}_i - \overline{S}_j \right)^2 \Big/ NA_1$, $\overline{S}_i = \sum_{j=1}^{N} S_{ij} \Big/ N$, and $\overline{S}_j = \sum_{i=1}^{A_1} S_{ij} \Big/ A_1$; "—" denotes an average value. S , i.e. the population of size A_1, is an A_1-by-N sample matrix whose element has the sample value $S_{i,j}$. δ is a constant to control the amount of the change in the mutation probability for every generation. The mutation probability P_m is held in the range of $\left[P_m^{Lower}, P_m^{Upper} \right]$. If the instant probability P_m is larger than the upper mutation probability P_m^{Upper} or smaller than the lower mutation probability P_m^{Lower} , the current probability P_m is reset to the initial value to continue the process. The number of mutation points is $P_m \cdot A_1$, which is rounded off to an integer. The mutation points are randomly selected from the population of size A_1. The values of the elements for the selected mutation points are randomly changed to an integer value at the range of 1 to *K*. The mutated population of size A_1 together with the best one chromosome is merged to have the population of size $A_1 + 1$.

A.5 Fitness Evaluation

The fitness is defined as the required transmit power. In the evaluation of the fitness for each chromosome in the population of $A_1 + 1$, a bit loading approach by using the water-filling technique is employed. It is the optimal algorithm to load bits in a single-user environment (Hughes-Hartogs, 1989) (Lai et al., 1999). As each chromosome has the solution of the subcarrier assignment for each user, the water-filling technique can be applied to solve the bit loading problem. After the fitness evaluation, one chromosome with the worst fitness is deleted if the best chromosome is updated. If the best chromosome is not replaced, the one identical to the best chromosome in the population of size A_1 is deleted. The population size is still A_1 for the next generation.

Finally, we iteratively perform the previous steps until the algorithm reaches the convergence condition.

B. Natural Selection Scheme II (NSS-II)

The second natural selection scheme is adapted from (Wang et al., 2005) with further investigation and detailed discussions. The performance will be compared with that of the proposed *NSS-I* in the simulation results. The related recombination and the mutation operations are addressed below.

B.1 Initialization of the population

The scheme presented in (Wang et al., 2005) has suggested that good genes should be added in the initial population to improve the convergence rate. For fair comparisons, the initial populations of the size B_1 are also composed of one chromosome generated by the CIA procedure (Wong et al., 1999b) and $B_1 - 1$ chromosomes generated by the randomized assignment. The representation for the solution is the same as in Table 1 with integer-values.

B.2 Selection

After sorting, B_2 chromosomes associated with the B_2 largest values of the fitness evaluation are selected from the population of size B_1. B_2 is the population size of the selected chromosomes. The remaining $B_1 - B_2$ chromosomes are saved in the mating pool. Besides, the best one chromosome is also kept independently in order to hold the convergence of solutions.

B.3 Recombination

One half of the $B_1 - B_2$ chromosomes are selected as parents by the following procedure, and then the two-point crossover by the rank weighting (Spears, 2000) is performed in our implementation. The first step is to give a random value for each chromosome. After sorting

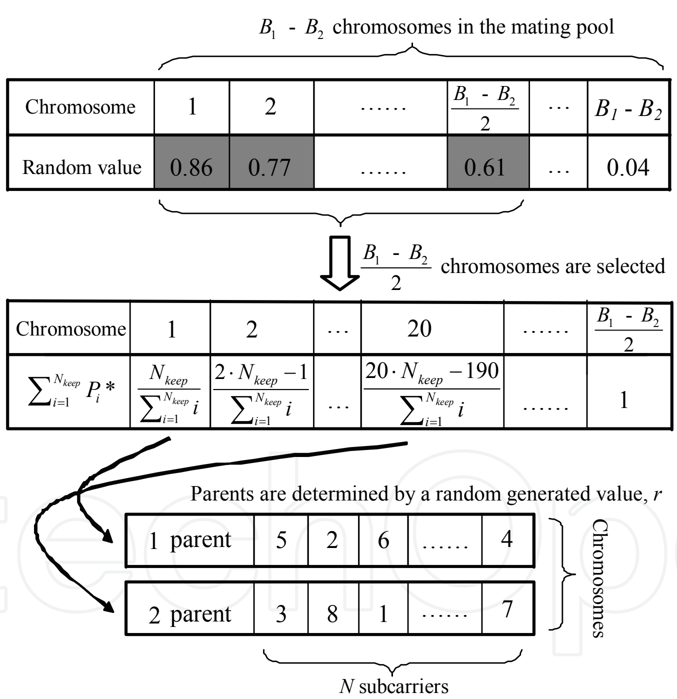

Fig. 2. Illustration of the recombination operation

the random values associated with the chromosomes, the first half of the $B_1 - B_2$ chromosomes are selected as parent chromosomes while the others are deleted. After choosing chromosomes, the rank weighting method is to produce a probability P_i* for each chromosome and the cumulative probability is obtained by $\sum_{i=1}^{N_{keep}} P_i*$. The chromosomes are selected from the mating pool to produce new offsprings. Here is the definition of the probability for each chromosome, P_i*:

$$P_i^* = \left(N_{keep} - i + 1\right) \Big/ \sum_{i=1}^{N_{keep}} i \tag{14}$$

Where i stands for an index of a chromosome; N_{keep} is the value of $(B_1 - B_2)/2$. A randomly generated value, *r*, is to check if *r* is between P_i^* and P_{i+1}^*. If it is true, chromosome i associated with P_i^* is selected as one parent. The above process of generating a random number *r* is repeated in order to find a pair of chromosomes. Figure 2 illustrates the procedure of the parent chromosomes' selection. The two chromosomes are selected as parents to perform the two-point crossover. There are $(B_1 - B_2)/2$ offsprings generated. The recombination operation in *NSS-I* considers the similarity and the difference between two chromosomes. It makes *NSS-I* more efficient than the recombination operation in *NSS-II*. The effect can be observed in the simulation.

B.4 Mutation

The concept of the mutation is to prevent the solution trapped into a local minimum. The mutation points are randomly selected from the merged population of size B_1, which is composed of the B_2 chromosomes, the $(B_1 - B_2)/2$ parent chromosomes, and the $(B_1 - B_2)/2$ new offsprings. The population size in the mutation step is $B_1 = B_2 + {B_1 - B_2}\big/2 + {B_1 - B_2}\big/2$.

The mutation probability P_m^* is adjusted adaptively. The mutation probability is increased if no better chromosomes are found in the consecutive generation. The parameters are set in the same manner as (Wang et al., 2005). The mutation probability P_m^* is held in the range of $\left[P_m^{Lower*}, P_m^{Upper*}\right]$. The mutated population of size B_1 together with the best one chromosome is the population of size $B_1 + 1$.

B.5 Fitness Evaluation

Before the evaluation of the fitness for each chromosome, the best one chromosome in the last generation is added. Again, in the evaluation of the fitness for each chromosome in the population of size $B_1 + 1$, the water-filling technique (Hughes-Hartogs, 1989) (Lai et al. 1999) is used to load bits to subcarriers. After the fitness evaluation, one chromosome with the worst fitness is deleted if the best chromosome is updated. If the best chromosome is not replaced, the one identical to the best chromosome in the population of size B_1 is deleted. The population size is B_1 for the next generation. Finally, we repeat the previous steps until the algorithm achieves the convergence condition.

C. Local Refinement Strategy

Referring to Fig. 1, the local refinement strategy (LRS) is performed after the fitness evaluation. For a given solution associated with a chromosome, some subcarrier assigned to a user may not be employed if the situation of no modulation (no transmission) on that subcarrier occurs. It means that the channel condition of this specific subcarrier is relatively bad for the user. The specific subcarrier is set to be free in our proposed approaches. The step of LRS is proposed to enhance the performance by re-allocating the free subcarrier to another user. It is to assign the specific subcarrier to a user who provides the maximum total transmit power reduction. After the operation of the bit loading for the chromosomes, then we check if there is a free subcarrier $\tilde{n}$ which has been assigned to user $\tilde{k}$. The free subcarrier is assigned to user k which results in the maximum required total transmit power reduction. After the subcarrier re-assignment operation, the process continues until there is no free subcarrier.

D. Adaptive Scheme

As wireless channels vary gradually but slowly for this type of allocation problems, the channel fading condition could be similar in adjacent allocation time slots. Based on this concept, the solutions obtained in adjacent allocation time slots could be similar. Owing to the property of wireless channels, the final solution of the previous processing time slot may be included in the initial population for the current time slot allocation process to speed up the convergence rate. If a better solution is applied in the initial population, the evolutionary algorithm-based schemes could converge faster and the population size could be reduced in the adaptive manner. The computational time would be further improved because of less possible candidate solutions and less generations to provide competitive performance. With the adaptive manner, the proposed algorithm may be performed with a large number of generations and a large population size in the first allocation time slot. In the followed consecutive allocation time slots, the final solutions in the last allocation time slot are utilized as a portion of the initial population in the current allocation time slot. As a smaller size of population and a smaller number of generations are employed to perform the algorithm to obtain the final solution, the computation cost can be reduced.

5. Simulation results

The frequency selective wireless channel model used in (Dong et al., 2001) is adopted. Perfect channel estimation is assumed. Each user has the same requested data rate. The channel power of the received signal for each user is varied because of the various path losses at the different locations. The set of the switching levels in (Torrance & Hanzo, 1996) for the modulation types is employed. All the following experiments are conducted under the channel conditions with the same statistics. The simulation parameters are listed in Table 5. In the initialization of the population, the numbers of subcarriers assigned to users are equal. The subcarriers are assigned to users by the CIA procedure (Wong et al., 1999b) and the randomized assignment. For fair comparisons, the sizes A_1 and B_1 of the initial populations are the same. The ratio $\mu / A_1 \approx 1/7$ is selected in our proposed scheme according to a selection mechanism (Siu et al., 2005). The mutation probability in the *NSS-I* scheme can be set small because the new offspring of size A_2 are formed by μ chromosomes with higher fitness. The parameters for *NSS-II* are set in the same manner as (Wang et al., 2005). In the simulation, the chromosome lengths are equal to the number of total subcarriers. Each element in the chromosome contains a user index which means a subcarrier allocated to the user. The chromosome length is fixed. Table 3 is an example of a 3-bit encoding scheme for the binary-string representation. By taking the first chromosome in Table 1 for example, the binary-string representation is obtained by using Table 2. This is the way we encode the chromosomes in the simulation.
The simulation results are displayed for the performance comparison among various schemes including the Wong's subcarrier allocation (SA) (Wong et al., 1999b) algorithm plus the optimum bit loading with the equal numbers of subcarriers for each user. The Wong's subcarrier allocation (SA) algorithm (Wong et al., 1999b) includes the constructive initial assignment (CIA) and the subcarrier swapping two steps to provide sub-optimal

performance. CIA, which is adopted as an initial subcarrier allocation method for one chromosome, needs to pre-assign the numbers of subcarriers for each user. It is temporarily set for the proposed scheme and will be adjusted during the process. The optimal allocation solutions as the performance bound are obtained by using the linear integer programming-based branch-and-bound algorithm (BnB) (Kim et al., 2006) (Wolsey, 1998). In the following simulation, 8-bit encoding is employed for the schemes with the binary-string representation.

Number of users	3, 4, 6, 8
Modulation types	0, QPSK, 16QAM, 64QAM
Symbol rate per subcarrier	250k symbols/s
Total Allowed Data rate	36 Mbits/s
Number of subcarriers	48
Center frequency	5 GHz
Frame duration	10 ms
$\{A_1, A_2, \mu, B_1, B_2, g_r, p_c\}$	$\{36, 31, 5, 36, 6, 0.5, 0.95\}$
$\{P_m^{Upper*}, P_m^*, P_m^{Lower*}, P_m^{Upper}, P_m, P_m^{Lower}, \delta\}$	$\{0.5, 0.1, 0.1, 0.05, 0.025, 0.01, 0.001\}$

Table 5. Parameters of Simulations

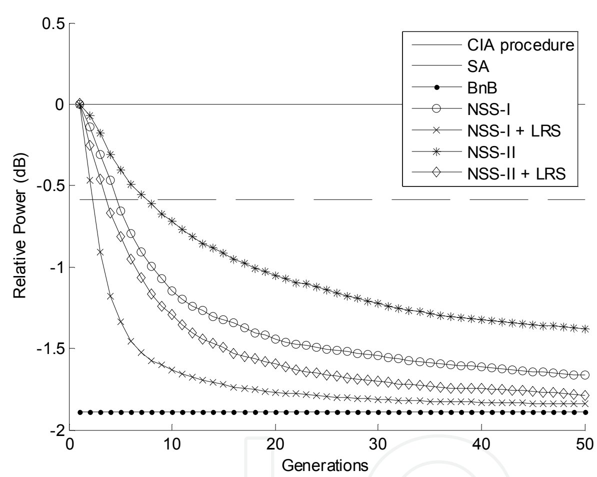

Fig. 3. Convergence comparison in terms of required transmit power for the proposed EA-based scheme with the real-valued representation for 6 users, the largest channel power difference among users = 30dB, and target BER=10^{-2}

The local refinement strategy, labeled *LRS,* is used in both EA-based schemes, *NSS-I* and *NSS-II* (Wang et al., 2005), with the integer representation. The local refinement strategy is proposed to enhance the convergence rate to the optimum solution. The convergence curves are plotted by averaging 100 trial runs with 50 generations to show the performance improvement of LRS in Fig. 3. The relative required transmit power for the best one chromosome is reduced as the number of generations increases because the best chromosome is kept independently. The convergence rates of *NSS-I + LRS* and *NSS-II + LRS* are faster than those of *NSS-I* and *NSS-II,* respectively. The simulation results in Fig. 3 demonstrate that the LRS truly improves the performance, and the performance of *NSS-I* is better than that of *NSS-II*. The result also shows that the proposed scheme, *NSS-I + LRS,* with the integer representation converges fast and is close to the optimum performance. After 50 generations, the performance of *NSS-I+LRS* is very close to that of *BnB*. By taking about 0.1 db point away from the BnB performance as an example, the number of the generations with the proposed scheme is about 25 generations. On the other hand, the other schemes require more than 50 generation to achieve that performance.

In Figs. 4 to 7, there are eight allocation schemes for performance comparison in the simulation, including five EA-based schemes, one suboptimal scheme (Wong et al., 1999b) (Wong et al., 1999b), the linear IP-based branch and bound scheme for the optimum performance bound (Kim et al., 2006), and an up-to-date genetic algorithm-based scheme (Reddy & Naraghi-Pour, 2007):**(1)** Scheme I: *NSS-II* + 8 bits encoding; **(2)** Scheme II: *NSS-II* + *LRS* + 8 bits encoding; **(3)** Scheme III: *NSS-II* + The integer encoding; **(4)** Scheme VI: *NSS-II* + *LRS* + The integer encoding; **(5)** Scheme V: *NSS-I* + *LRS* + The integer encoding; **(6)** SA (Wong et al., 1999b); **(7)** BnB (Kim et al., 2006); **(8)** GA (Reddy & Naraghi-Pour, 2007).

The simulation results are averaged over 100 trial runs with 200 generations and are shown in Figs. 4 to 7 for different channel power differences, different target BERs, and different numbers of users. Figs. 4 to 7 reveal the similar performance trend can be observed in the results. The detailed comments regarding the performance comparison are as follows:

1. The difference between Scheme I and Scheme III is the solution presentation. The performance of Scheme III with the integer representation is better than that of Scheme I with the binary-string representation at the same generation. It also reveals that the scheme with the integer representation outperforms the scheme with the binary-string representation. The EA-based schemes with the integer representation are more suitable for solving the resource allocation problems. Even if the local refinement strategy is employed, similar results with the effect of the representation can be observed (Scheme II and VI).
2. The effects of the design in the recombination and the mutation operations are also investigated. The performances of Scheme VI and Scheme V indicate that the recombination and the mutation operations affect the performance. It reveals that the proposed recombination operation and the mutation operation can achieve better performances. The performance of the proposed Scheme V is very close to that of the optimum solution.
3. The proposed local refinement strategy can improve the performance. In addition to the convergence rate improvement, Scheme II and Scheme VI outperform Scheme I and Scheme III in terms of transmit power. The performances of the proposed Scheme V are even closer to those of the optimum solutions.
4. Besides the fast convergence feature demonstrated in Fig. 3, the simulation results in Figs. 4 to 7 show that the performances of the proposed HEA-based scheme with the integer representation, Scheme V, are close to those of the optimum solutions with the judicious designs of the recombination operation, the mutation operation, and the local refinement strategy.
5. The GA-based scheme (Reddy & Naraghi-Pour, 2007) outperforms Scheme I and Scheme III in terms of transmit power when a fewer number of users is considered. When the proposed local refinement strategy is employed to Scheme I and Scheme III, i.e. Scheme II and Scheme IV, their performances are greatly improved and better than those of GA-based scheme (Reddy & Naraghi-Pour, 2007). The major proposed hybrid evolutionary algorithm-based scheme, Scheme V, performs best and the performances are the closest to those of the optimum solutions in these simulations.

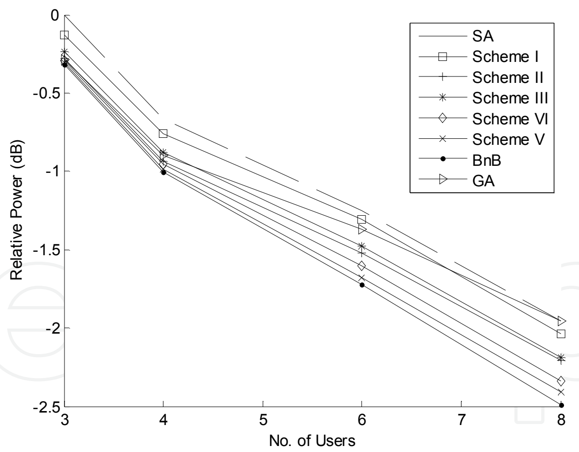

Fig. 4. Performance comparison in terms of required transmit power among eight allocation schemes, the largest channel power difference among users = 15dB, and target BER= 10^{-2}

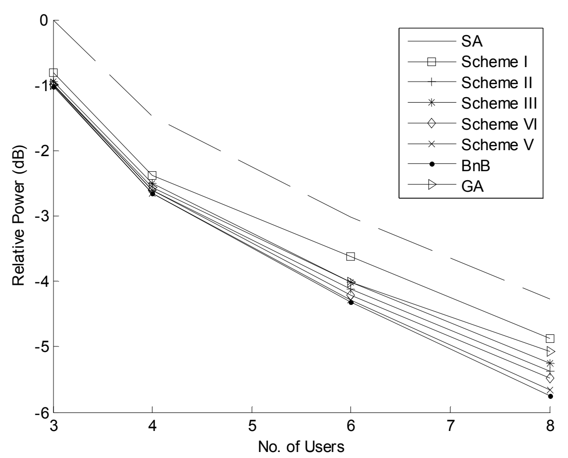

Fig. 5. Performance comparison in terms of required transmit power among eight allocation schemes, the largest channel power difference among users = 30dB, and target BER= 10^{-2}

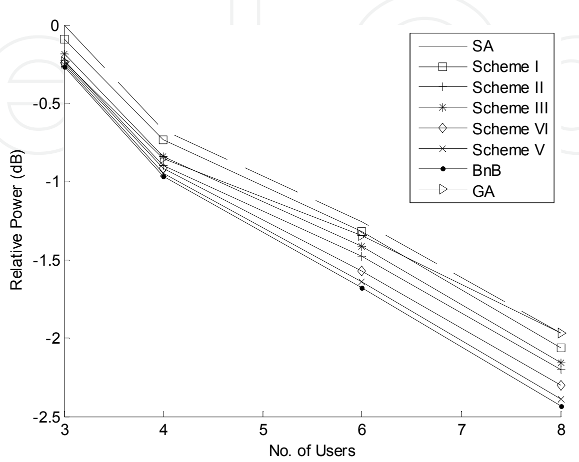

Fig. 6. Performance comparison in terms of required transmit power among eight allocation schemes, the largest channel power difference among users = 15dB, and target BER= 10^{-2}

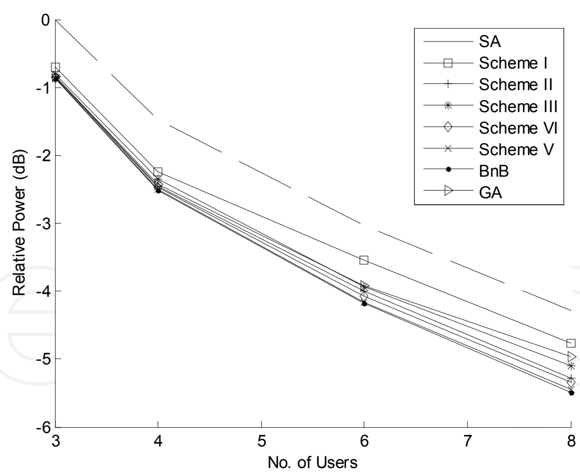

Fig. 7. Performance comparison in terms of required transmit power among eight allocation schemes, the largest channel power difference among users = 30dB, and target BER= 10^{-2}

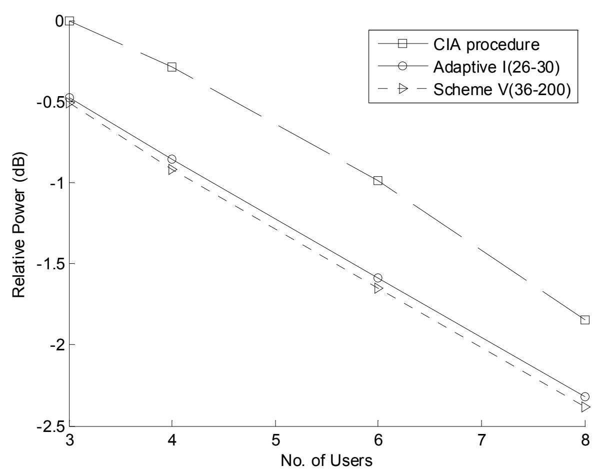

Fig. 8. Performance comparison with the adaptive scheme in terms of required transmit power at mobile speed=1km/h, the largest channel power difference among users = 15dB, and target BER= 10^{-2}

The simulations are conducted to demonstrate the efficacy of the adaptive scheme which can reduce the number of the generations and the population size to provide competitive performance in various adaptive situations. The mobile speed is 1km/h. The allocation period is on a per frame basis. The scheme labeled "Adaptive I" considers that the final solutions of the previous processing frame are included in the initial population for the current frame allocation process. The proposed scheme labeled "Scheme V" is compared to demonstrate the efficacy of the adaptive scheme in the reduced computational cost to provide competitive performance. In the figures, the two parameters (a-b) inside the parenthesis denote the population size and the number of generations. The population size A_1 =26; 30 generations are executed; 5 best solutions obtained after 200 generations in the previous frame are included in the initial population. As performed with fewer generations and a smaller population size, there is performance degradation between Adaptive I and Scheme V. However, the performance degradation is less than 0.1 dB in Fig.

8. Fig. 9 reveals the similar performance trend but even closer to that of the Scheme V, where the largest channel power difference among users is increased.

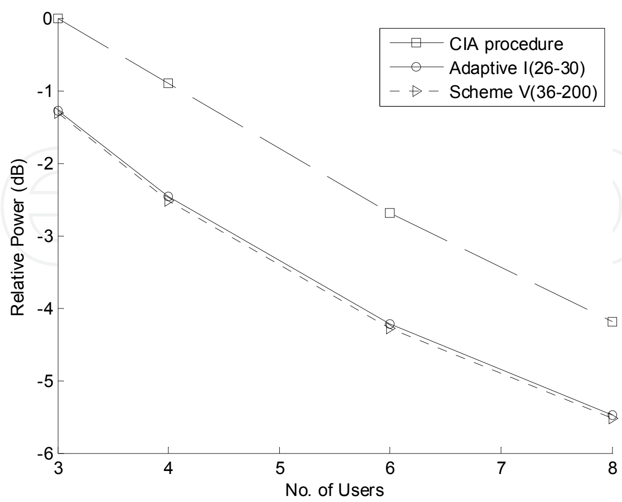

Fig. 9. Performance comparison with the adaptive scheme in terms of required transmit power at mobile speed=1km/h, the largest channel power difference among users = 30dB, and target BER= 10^{-2}

In Figs. 10-11, 100 ms is the duration to perform the algorithm. The scheme "Adaptive II" obtains the solution for the first frame with 200 generations. The algorithm is performed with the smaller number of generations and the smaller size of population for the followed consecutive 9 frames. As indicated in the simulation results, the adaptive scheme tracks the channel variations well and provides very competitive performance compared to the scheme with the full number of generations = 200 and the full size of population = 36 of scheme V.

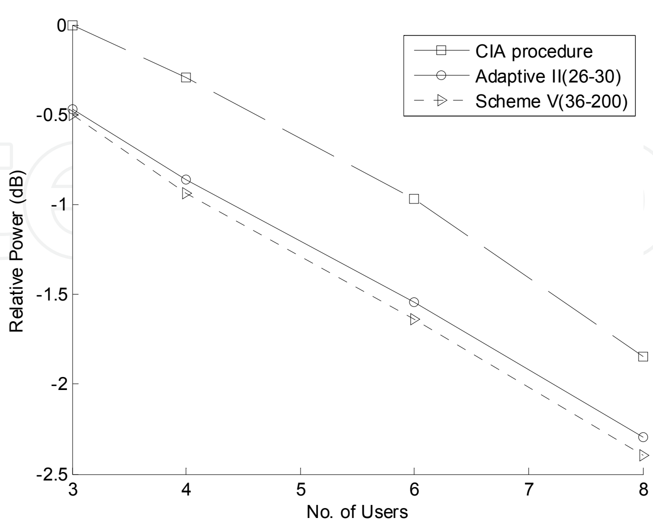

Fig. 10. Performance comparison to demonstrate the tracking capability in terms of required transmit power at mobile speed=1km/h, the largest channel power difference among users = 15dB, and target BER= 10^{-2}

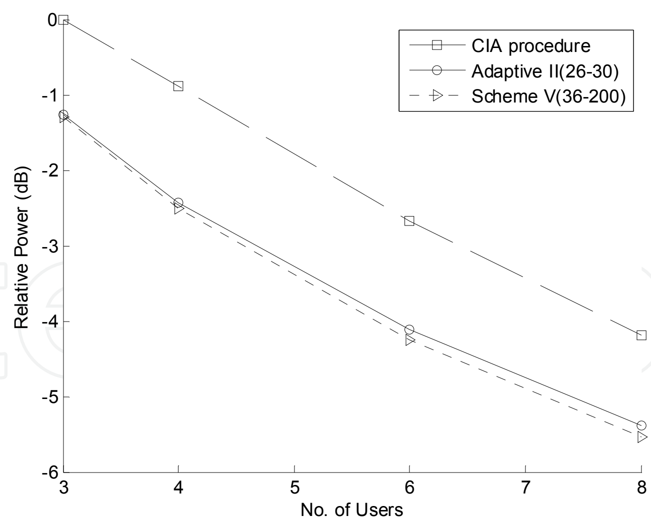

Fig. 11. Performance comparison to demonstrate the tracking capability in terms of required transmit power at mobile speed=1km/h, the largest channel power difference among users = 30dB, and target BER= 10^{-2}

In the next simulation to demonstrate the tracking capacity with the scheme, "Adaptive III", the frame duration is switched to 5 ms which is employed in WIMAX standard and a carrier frequency of 1.95 GHz in the PCS (Personal Communication Services) band is adopted. The channel duration for the simulation is 1 second. The algorithm is performed with 200 generations for the solution of the first frame while being performed with 30 generation for those of the rest of the frames to provide the solutions. As displayed in Figs. 12-13, the performances are very close to those of Scheme V with the full number of generations and the full size of population per each frame operation.

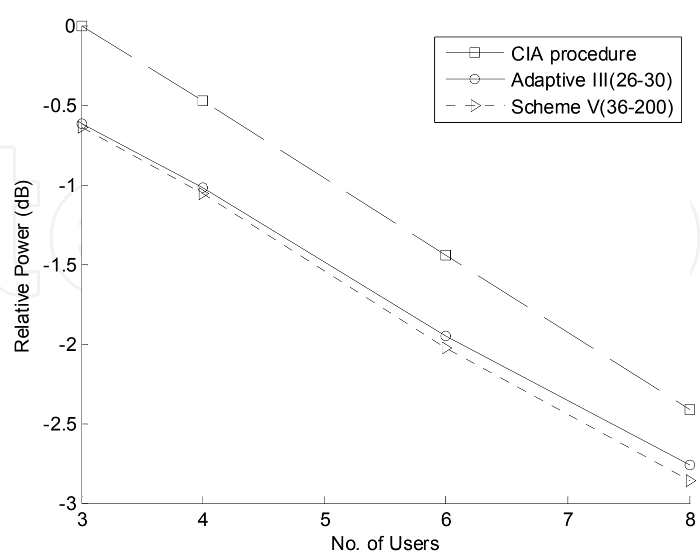

Fig. 12. Performance comparison to demonstrate the tracking capability in terms of required transmit power at mobile speed=1km/h, the largest channel power difference among users = 15dB, and target BER= 10^{-2}. Frame duration = 5 ms, carrier frequency = 1.95 GHz

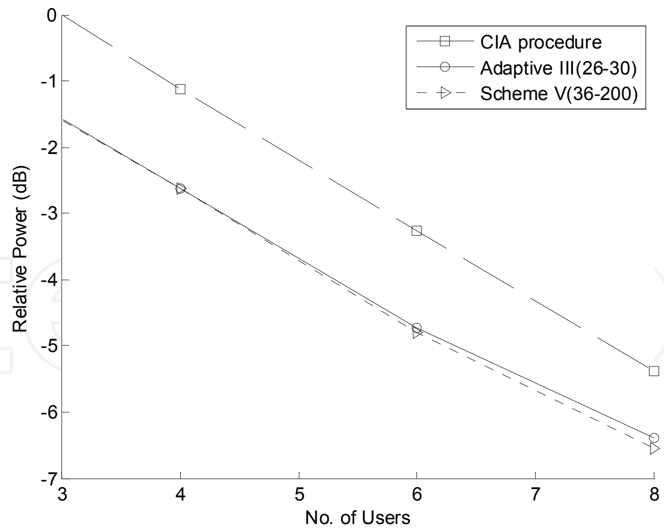

Fig. 13. Performance comparison to demonstrate the tracking capability in terms of required transmit power at mobile speed=1km/h, the largest channel power difference among users = 30dB, and target BER= 10^{-2}. Frame duration = 5 ms, carrier frequency = 1.95 GHz

6. Conclusion

This paper proposes a hybrid evolutionary algorithm-based scheme to solve the subcarrier, bit, and power allocation problem. The hybrid evolutionary algorithm is an evolutionary algorithm-based approach coupled with a local refinement strategy. It is presented to improve the performance and offers the faster convergence rate. Simulation results show that the proposed hybrid evolutionary algorithm-based scheme with the integer representation converges fast, and the performance is close to that of the optimum solution with the judicious designed of the recombination operation, the mutation operation, and the local refinement strategy. An adaptive scheme for time-varying channels is also proposed to obtain the solution having competitive performance with the reduction of the population sizes and the number of generations.

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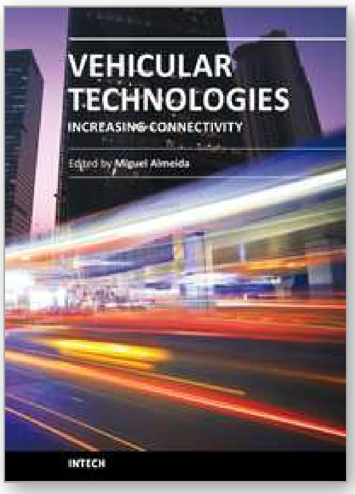

Vehicular Technologies: Increasing Connectivity
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This book provides an insight on both the challenges and the technological solutions of several approaches, which allow connecting vehicles between each other and with the network. It underlines the trends on networking capabilities and their issues, further focusing on the MAC and Physical layer challenges. Ranging from the advances on radio access technologies to intelligent mechanisms deployed to enhance cooperative communications, cognitive radio and multiple antenna systems have been given particular highlight.

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